PROJECT ID: eems019

U.S. DEPARTMENT OF ENERGY

SMARTMOBILITY

Systems and Modeling for Accelerated Research in Transportation

Smart Urban Signal Infrastructure and Control

Pillar: Urban Science

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Oak Ridge National Laboratory
2019 DOE Vehicle Technologies Office Annual Merit Review
11 June 2019

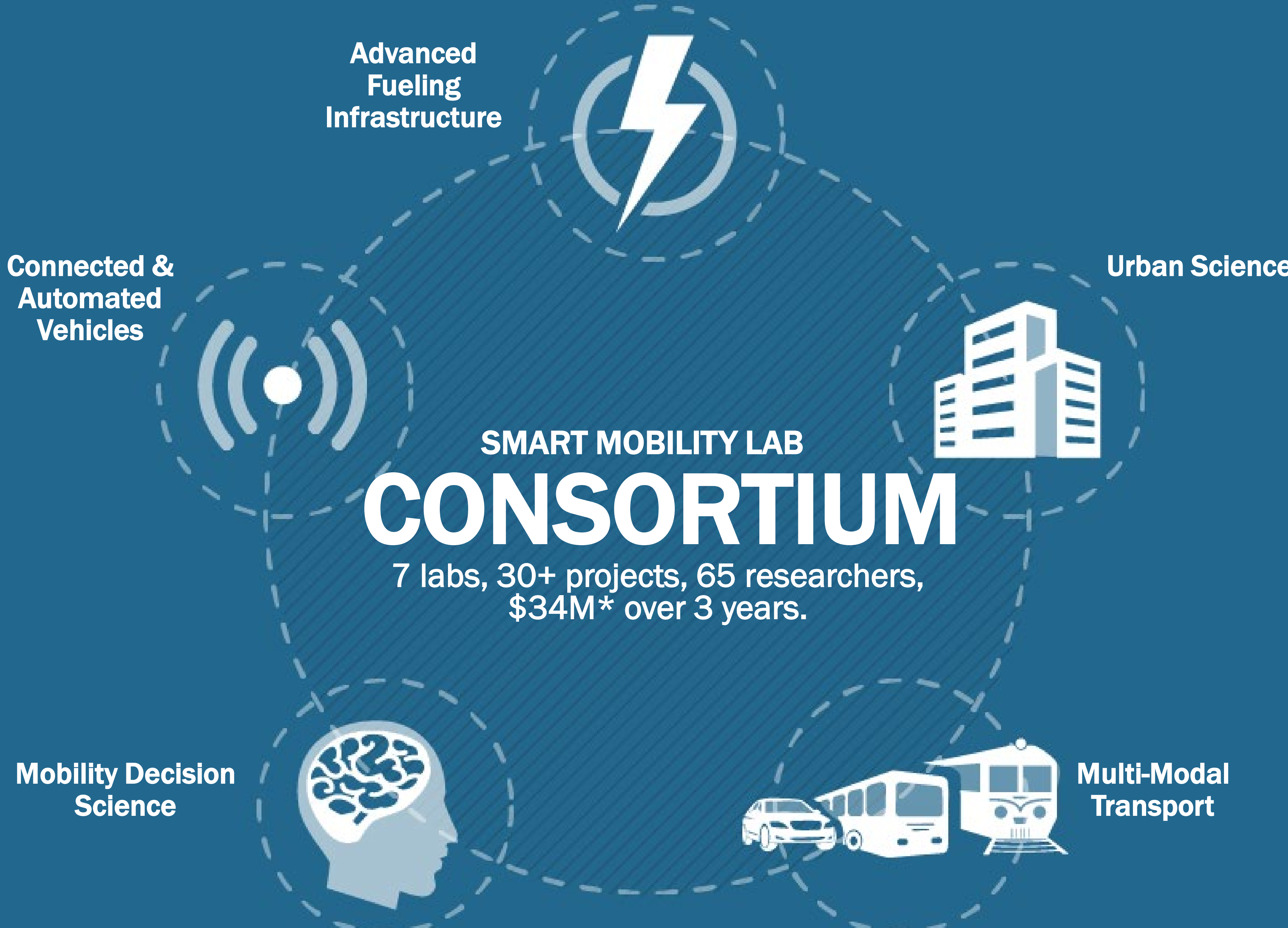
Argonne NATIONAL LABORATORY · INL Idaho National Laboratory · BERKELEY LAB · OAK RIDGE National Laboratory · NREL NATIONAL RENEWABLE ENERGY LABORATORY

ENERGY EFFICIENT MOBILITY SYSTEMS PROGRAM INVESTIGATES

MOBILITY ENERGY PRODUCTIVITY

THROUGH FIVE EEMS ACTIVITY AREAS

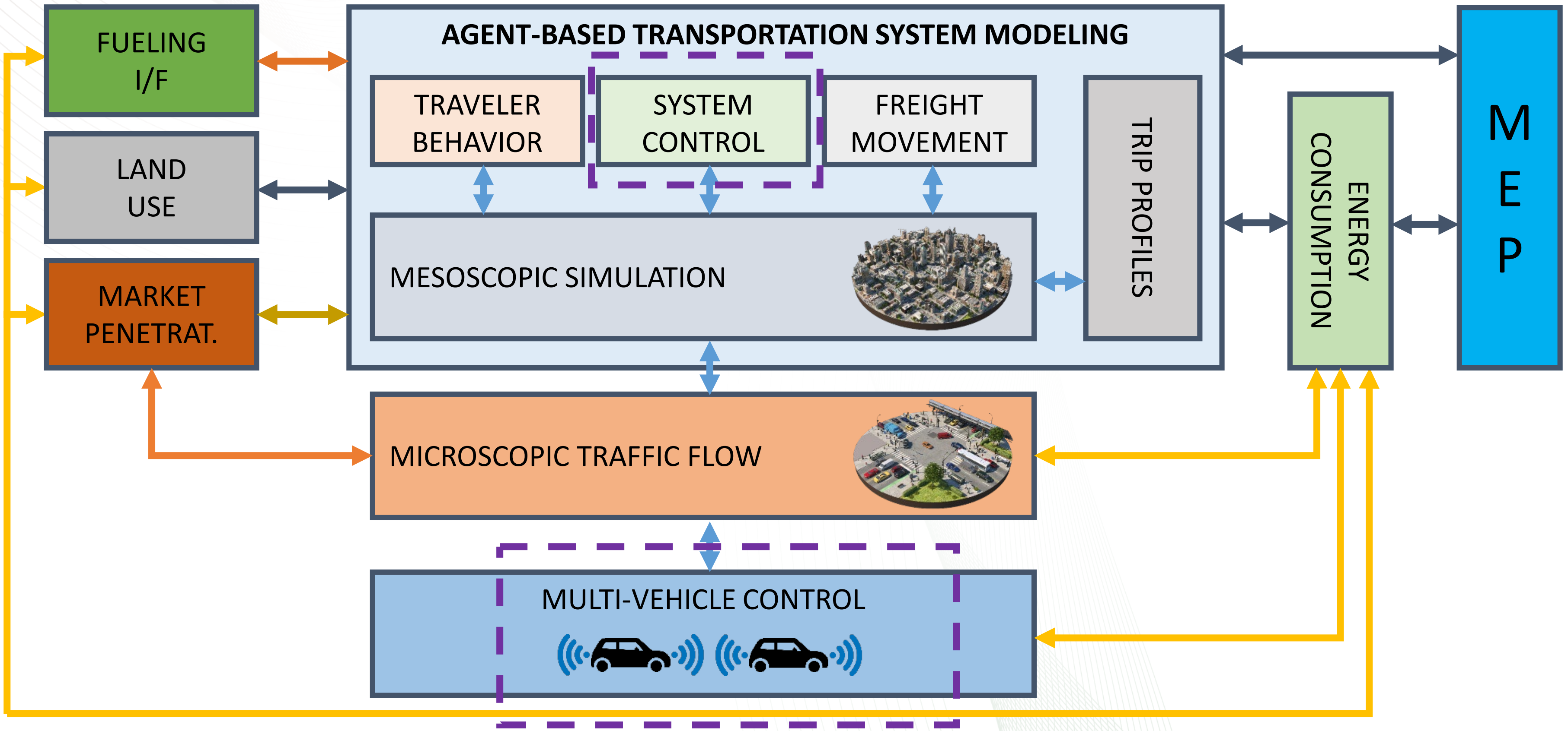
- Advanced R&D Projects
- Living Labs
- Smart Mobility Lab Consortium
- Core Evaluation & Simulation Tools
- HPC4Mobility & Big Transportation Data Analytics



*Based on anticipated funding

This project contributes to system control and multi-vehicle control aspects through micro-traffic flow

END-TO-END MODELING WORKFLOW



Overview

Timeline

- Project start date: 10/1/2016
- Project end date: 9/30/2019
- Percent Complete: 80%

[Milestone acheived for Quarter 2 in FY19]

Budget

- Total project funding:
  - DOE Share: $605K for FY19**
  - ORNL (250K + 175K)
  - NREL (180K)
  - Contractor share: NA

** Two EEMS projects are merged in FY19

Barriers

- Measuring the energy impacts of CAVs in urban signal networks and integrate energy goals in control algorithms,
- Computational difficulty of accurately simulating and optimizing large- scale network of signalized intersections,
- Execution of traffic control in a mixed traffic environment—CAVs and human drivers

Partners

- Project lead: ORNL
- Collaboration: NREL

Relevance/Objectives

- Overall objectives
  - Investigate the impact of optimized traffic signal systems in an Automated, Connected, Electric, and/or Shared (ACES) environment,
  - Develop robust and scalable signal control schemes leveraging connectivity,
  - Assess near-term safety-efficiency benefits from spatial sensing technologies.
- Objectives for FY19
  - To quantify the mobility and energy impacts of less than 100% CAV market share on the performance of developed control algorithms (TASK 1),
  - To build distributed control techniques for large networks (TASK 2),
  - To develop and evaluate stochastic distribution controls that can achieve smooth traffic flow and minimized energy consumption (TASK 3),
  - To assess the impact of spatial sensing at intersections (TASK 4).
- Impact
  - Provide an assessment of the impact of signal control optimization in an ACES environment accounting for market share and connectivity of CAVs.

Milestones and current status FY19

Milestone Name/Description	Criteria	End Date	Type	Status
Scenario development for testing sensitivity for control schemes—CAV and EV classes market share, and ASI (ORNL) (TASK-1)	A comprehensive array of scenarios/experiments accounting for CAV share	3/31/2019	Quarterly (Q2)	COMPLETE
Results/Report on the sensitivity of market penetration rate—partial information and electric vehicles (ORNL) (TASK-1)	Complete sensitivity analyses	6/30/2019	Quarterly (Q3)	ON TRACK (Results Done)
Development of distributed control for a 20-intersection network (ORNL) (TASK-2)	Demonstration in a large network	9/30/2019	Quarterly (Q4)	ON TRACK
Closed-loop stochastic distribution control implementation considering CAV market share (ORNL) (TASK-3)	Demonstration of Control with mobility and energy benefits	9/30/2019	Quarterly (Q4)	ON TRACK
Review/synthesis study of Energy Equivalence of Safety (NREL) (TASK-4)	Conference ready paper and presentation	3/31/3019	Quarterly (Q2)	ON TRACK
Draft White Paper that includes the literature review and framework for simulation of AIS (NREL) (TASK-4)	Delivered to NREL for review	5/31/2019	Milestone	ON TRACK
Final project report with findings for AIS – for paper submission (NREL) (TASK-4)	Submission to TRB Annual Meeting	8/1/2019	Deliverable	ON TRACK

Overview of tasks

Control of physical traffic Lights in a *Connected Environment*

Mobility and energy impacts from optimizing signal control

Develop control algorithms that leverage sensing capabilities and data availability (Task 1); Scalable (Task 2); Applicable to fully autonomous intersections (Task 3)

Task 1.1
Task 1.2

Impact of less than 100% market share of CAV

Vehicle based sensing (BSM)

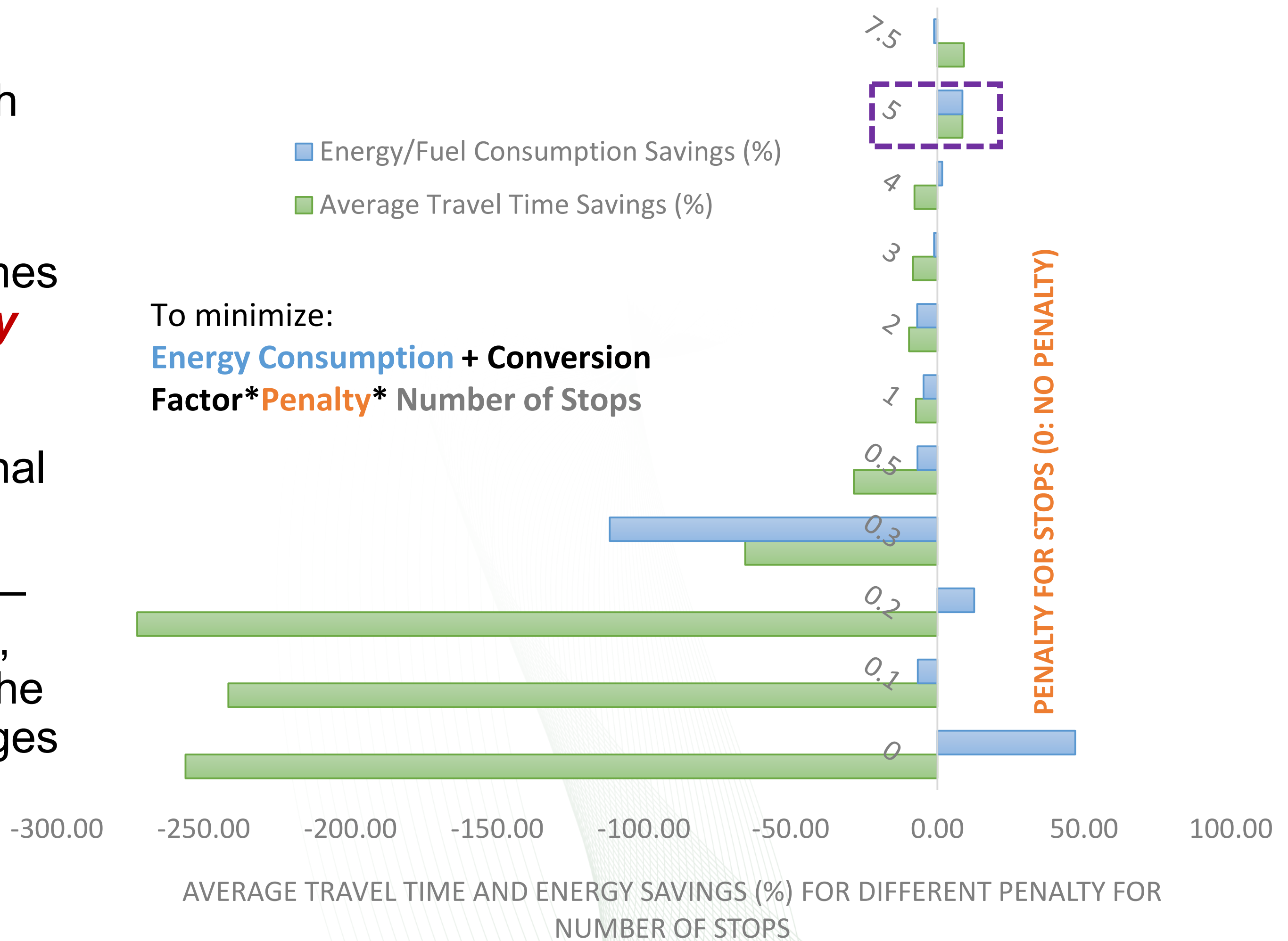
Impact of partial observability from advanced infrastructure sensing

Task 4.0

Infrastructure base sensing

Approach: Market share sensitivity for RL-based control (TASK-1)

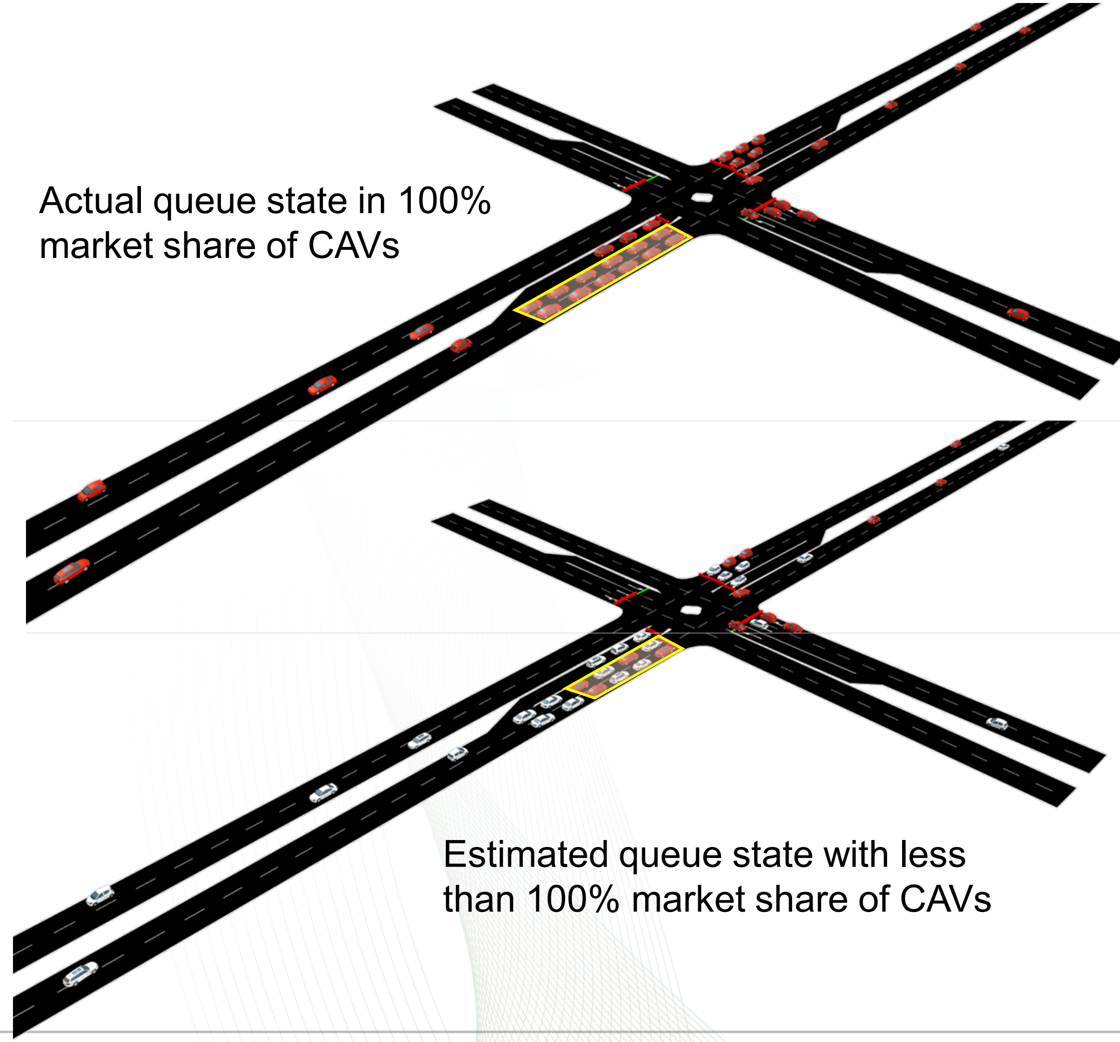
- Reinforcement learning(RL) based control algorithm with mobility and energy goals in FY 18**
- The algorithm assumes ***perfect connectivity and information sharing*** among the vehicles and the signal controller,
- Controllers observe—queue length, speed, and position—from the Basic Safety Messages broadcasted by the vehicles,



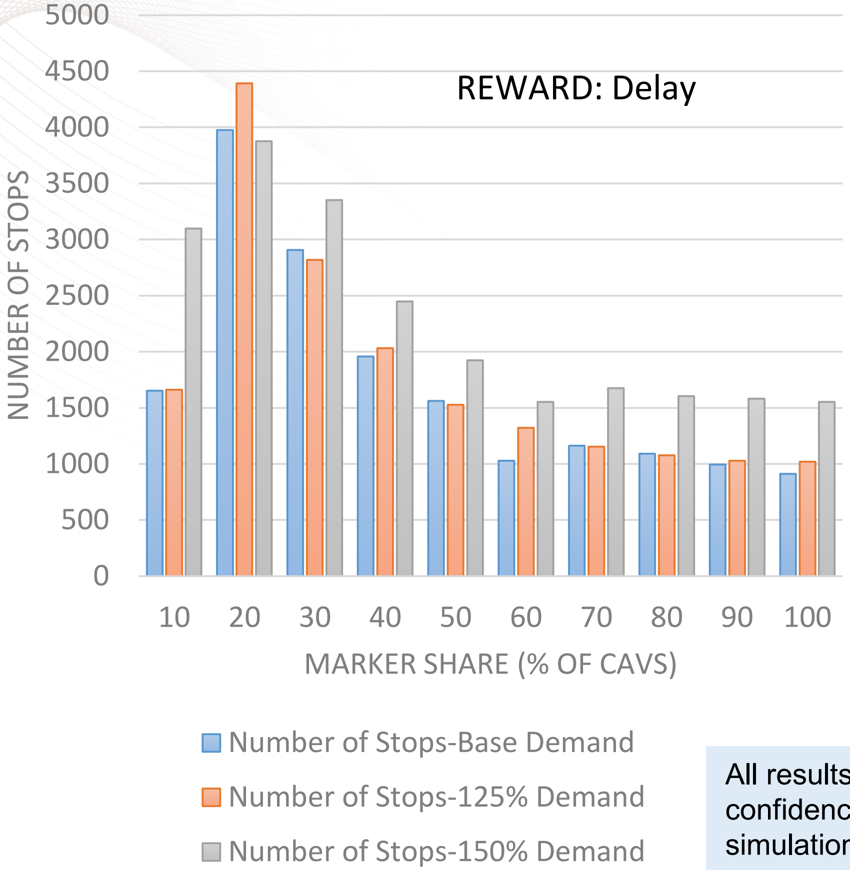
**Islam, SMA B. A., HM Abdul Aziz, Hong Wang, and Stanley Young. "Minimizing energy consumption from connected signalized intersections by reinforcement learning." In *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pp. 1870-1875. IEEE, 2018. 10.1109/ITSC.2018.8569891

Approach: Market share sensitivity for RL-based control (TASK-1)

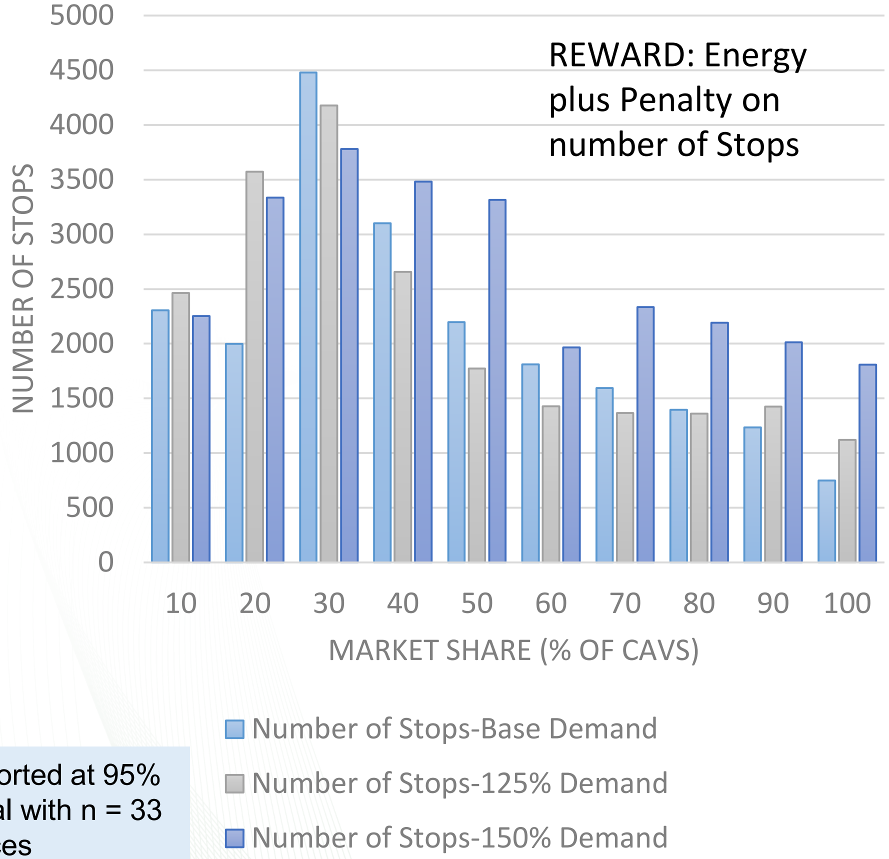
- Two vehicle classes:
  - CAV: Communicate and share information with the controller
  - Legacy: No data exchange with the signal controller
- We relaxed the assumption of ***perfect connectivity and information sharing*** among the vehicles and the signal controller,
- The signal controller can partially observe the environment—queue length, speed, and position—from the Basic Safety Messages broadcasted by the CAVs in the network



Findings—Number of Stops

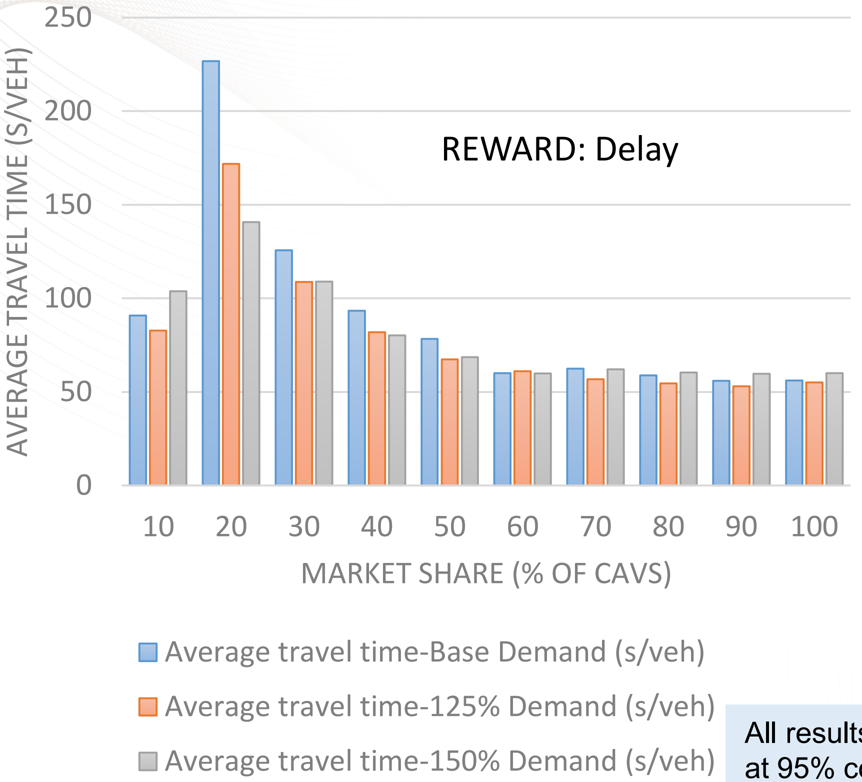


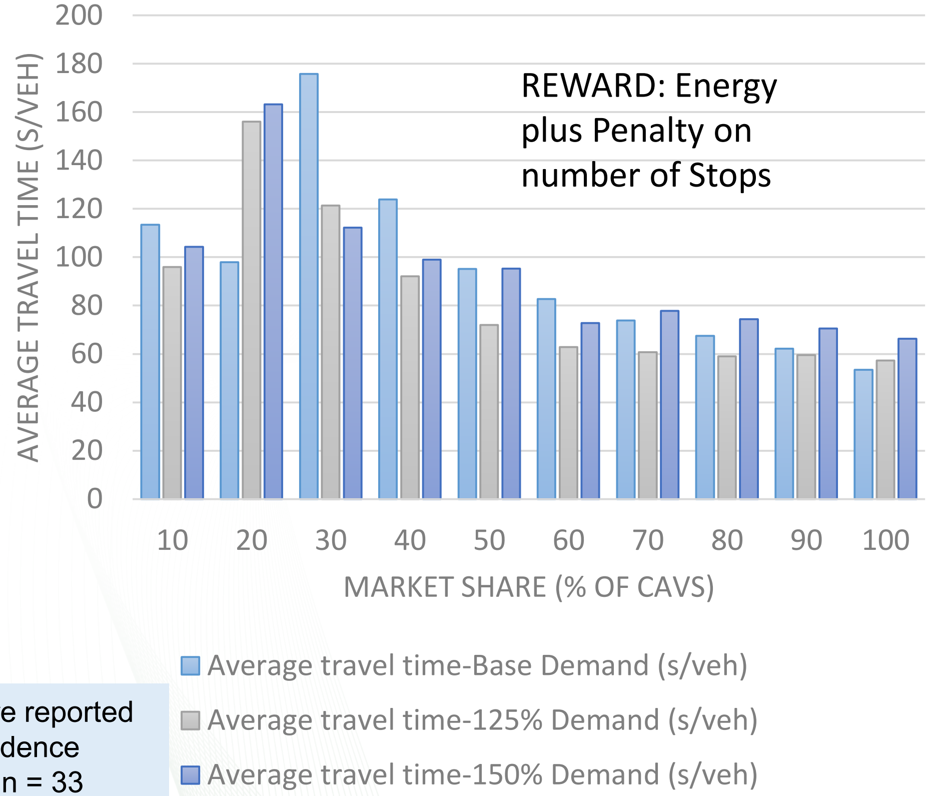
All results are reported at 95% confidence interval with n = 33 simulation instances



- Significant improvement when CAV marker share exceeds 30%,
- At low market share, no clear trend was found—mostly due the instability in the traffic state and corresponding learning of controllers.

Findings—Average Travel Time (seconds/vehicle)

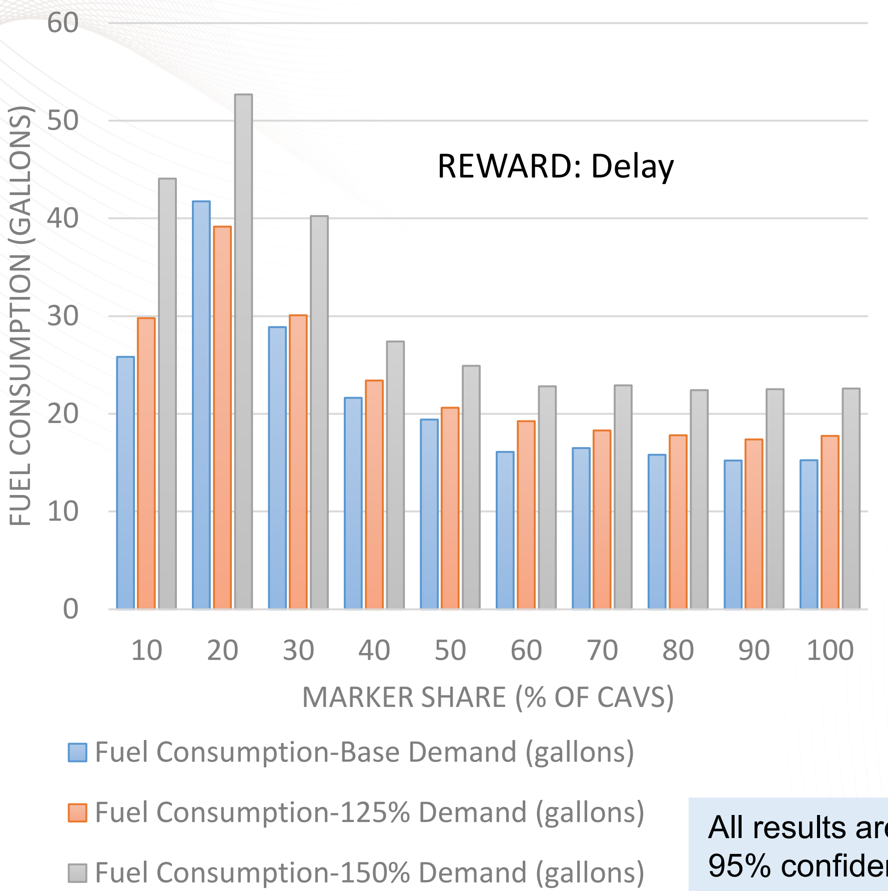


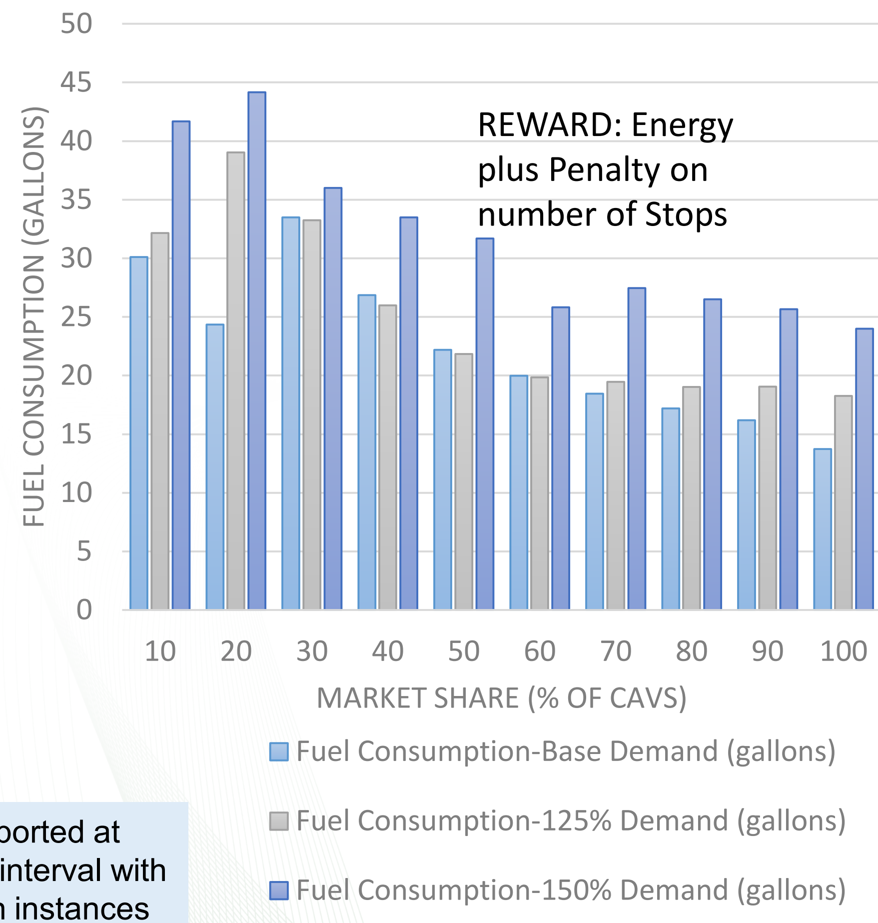


All results are reported at 95% confidence interval with n = 33 simulation instances

- For CAV market share less than 50%, performance is worse for low demand—low traffic volume increases the error margin for traffic state estimation,
- Improvements become marginal when the CAV market share is above 60%.

Findings—Energy/Fuel Consumption (gallons)





All results are reported at 95% confidence interval with n = 33 simulation instances

- Higher instability of traffic states at low market share,
- High impact on energy consumption when market share falls below 50%.

Approach: Stochastic-gradient approximation based optimization for large networks (TASK-2)

- Distributed algorithm for a network level optimization of delay with bounds on energy consumption
- Distributed optimization at intersection level**
- Gradient approximation-based optimization
  - Non-convex and non-linear energy consumption using vehicle-specific-power equations
- Spatial-queueing based traffic flow model—Cell Transmission Model
- Formulation:

$$P1: \min D(\boldsymbol{\theta})$$

$$\text{subject to } E(\boldsymbol{\theta}) \leq E_a$$

Where,

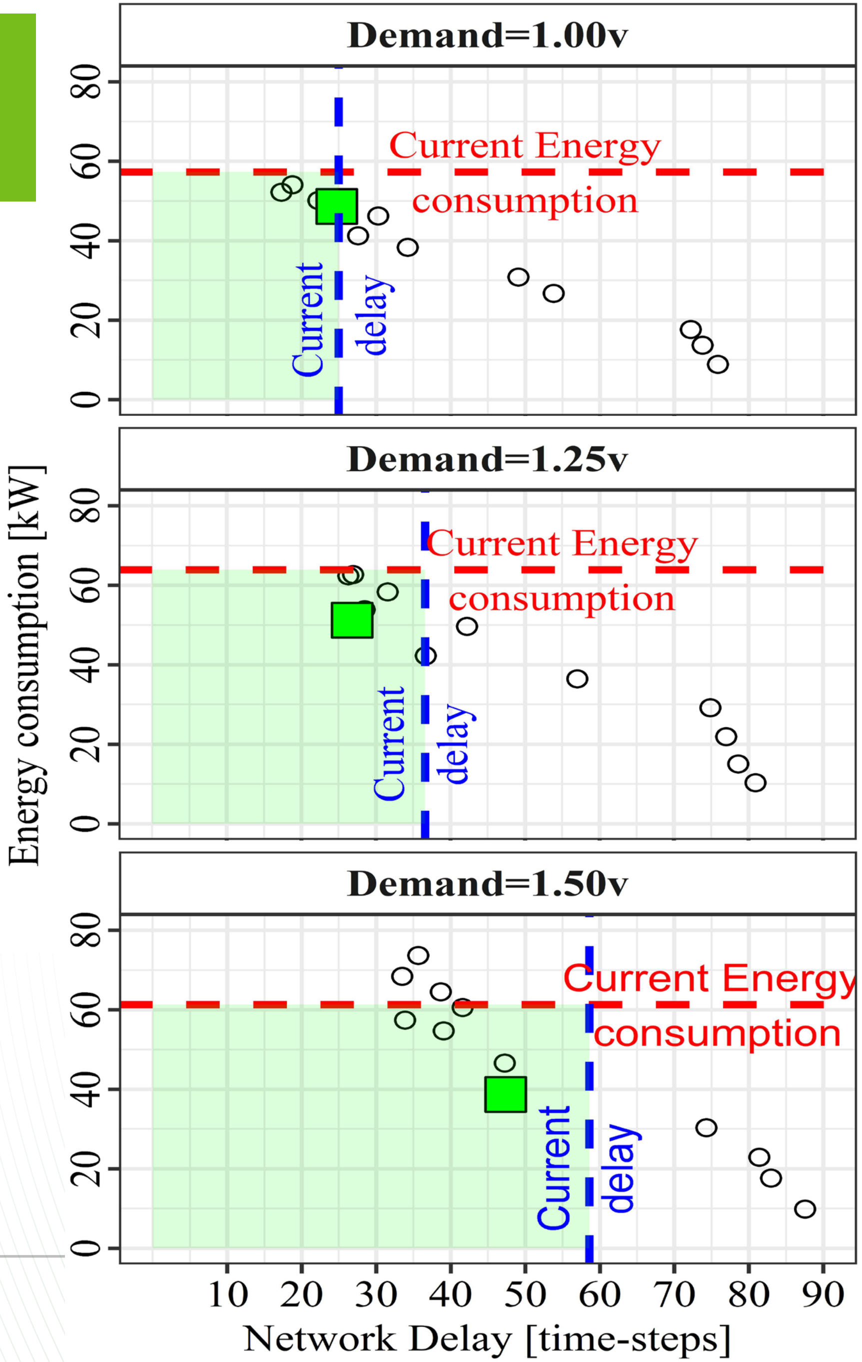
$D(.)$:	Total network delay,
$E(.)$:	Total energy consumption in the network,
E_a:	Allowable energy consumption in the network,
$\boldsymbol{\theta}$:	Vector of control variables to be optimized.

**Islam, SMA Bin Al, and Ali Hajbabaie. "Distributed coordinated signal timing optimization in connected transportation networks." *Transportation Research Part C: Emerging Technologies* 80 (2017): 272-285.

Initial results—Centralized SPSA: (TASK-2)

Network performances of constrained SPSA algorithm are compared with existing signal control system in a test network for three demand patterns. The Red and blue dotted lines show the energy consumption and delay in Lankershim Boulevard, CA (NGSIM data from US DOT) with existing signal control system respectively. The shaded green areas show the regions where both delay and energy metrics are better compared with the existing control. The Green Square shows the best option for each demand level.

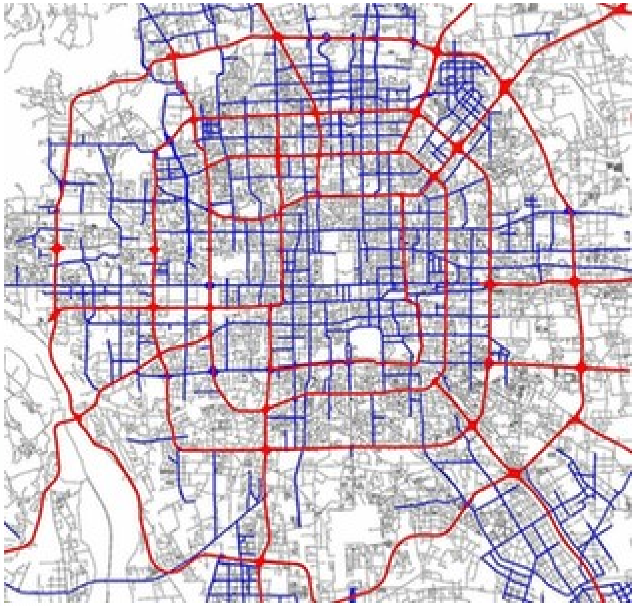
Cite as: S M A Bin Al Islam, H M Abdul Aziz, Ali Hajbabaie. (2019) Stochastic Gradient-based Optimal Signal Control with Energy Consumption Bounds, Submitted for publication (*in review*).



Approach: Stochastic Control—Smooth traffic flow for energy minimization (TASK-3)

Stochastic distribution control viewpoints

- Road Networks
- Intersections and Sensors
- Traffic Lights



All figures from google

A good traffic flow distribution = uniform distribution geographically

Approach: Stochastic Control—Smooth traffic flow for energy minimization (TASK-3)

Objective

For a networked intersections (say urban areas), develop signal timing strategy that makes the traffic flow (queue length distribution) as uniform as possible

Approaches:

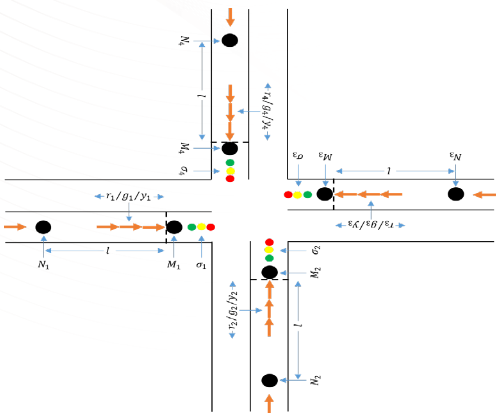
1) Modelling and stochastic distribution control that shapes the queue length probability density function have been completed for two intersections, where concept proof has been performed successfully;

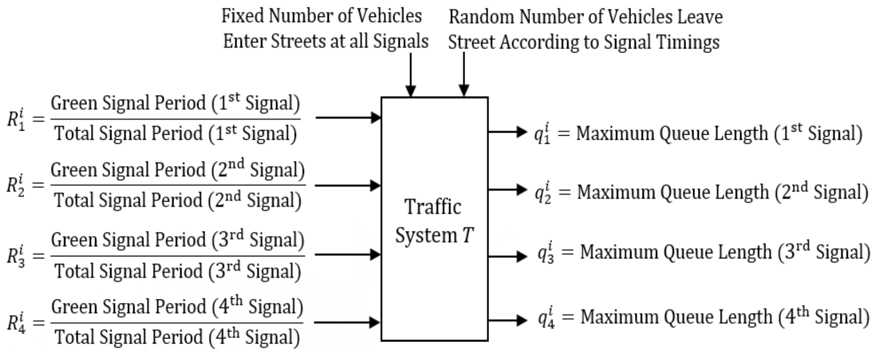
2) Modelling and control for 20+ intersections is being developed using multi-input and multi-output stochastic distribution control theory;

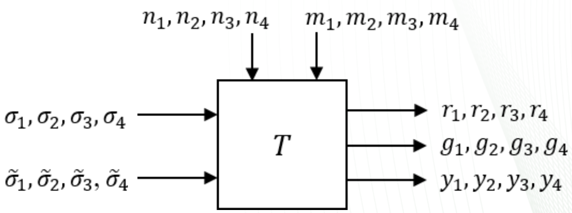
3) Simulation verification for the modelling and control strategy in 1) with collaboration of University of Washington and University of Virginia

H. Wang, Bounded Dynamic Stochastic Distributions Modelling and Control, Springer-Verlag (London) Ltd, March, 2000. (ISBN 1-85233-187-9, total page number: 176).

Approach: modeling of four-legged two-way Intersections (TASK-3)

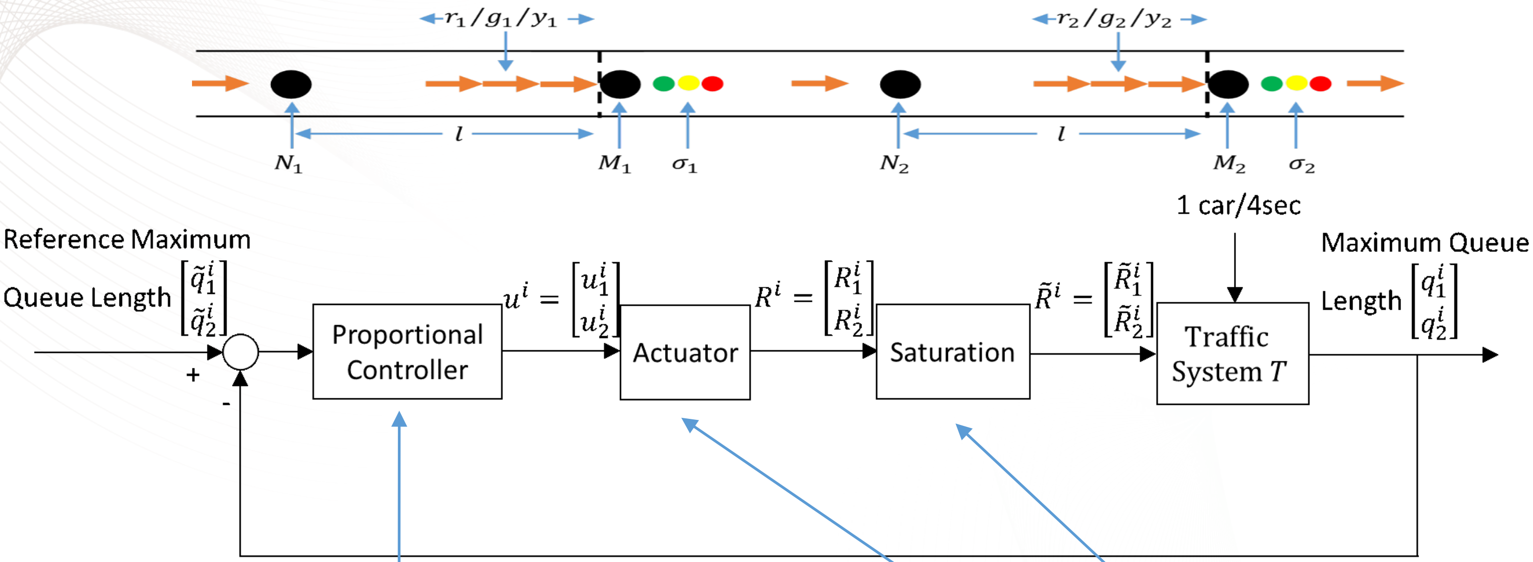






Recursive input-output traffic queue model and transfer function of one-signal corridor hold for all signals and corresponding streets independently of 4-signal intersection as well

Approach: Control of four-legged two-way Intersections (TASK-3)

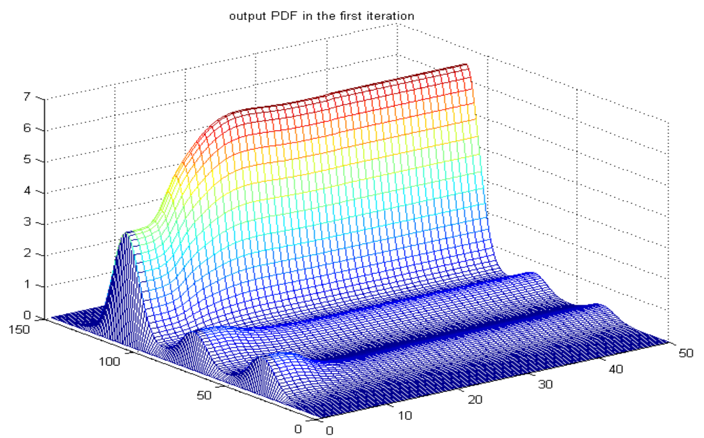


$$u^i = \begin{bmatrix} u_1^i = K_p\left(\tilde{q}_1^i - q_1^i\right) \\ u_2^i = K_p\left(\tilde{q}_2^i - q_2^i\right) \end{bmatrix}$$

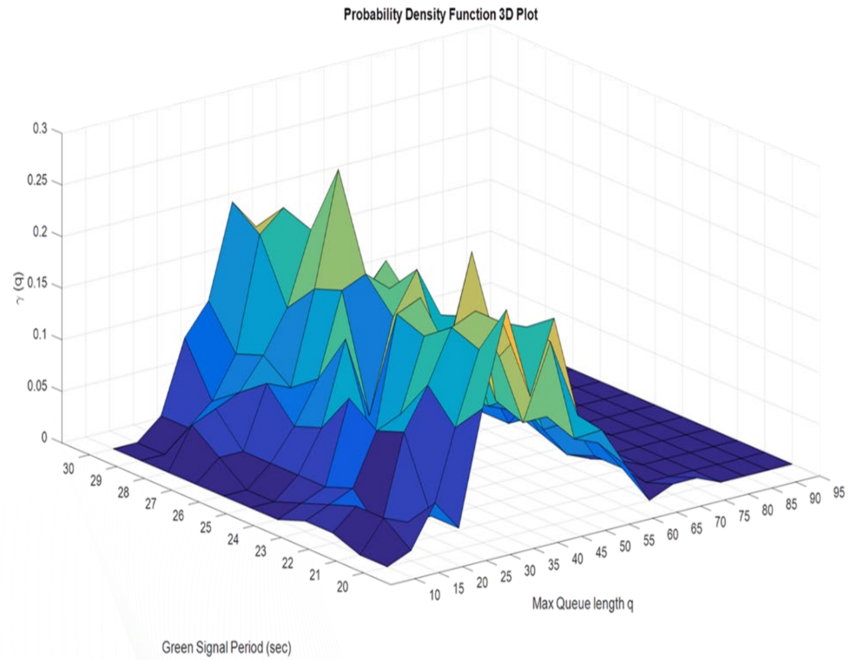
$$R^i = \begin{bmatrix} R_1^i = \dfrac{u_1^i - \left(\tilde{q}_1^i - \underline{q}_1\right)}{\left(\tilde{q}_1^i - \bar{q}_1\right) - \left(\tilde{q}_1^i - \underline{q}_1\right)} \\ R_2^i = \dfrac{u_2^i - \left(\tilde{q}_2^i - \underline{q}_2\right)}{\left(\tilde{q}_2^i - \bar{q}_2\right) - \left(\tilde{q}_2^i - \underline{q}_2\right)} \end{bmatrix}$$

Preliminary results: Stochastic Control—Smooth traffic flow for energy minimization (TASK-3)

- Smooth traffic flow over the concerned area would mean a minimum energy consumption
- This indicates that one need to use 3 layered structure to smooth the traffic flow and make the queue length a uniform distribution (see bottom figure).
- Taking into consideration that from the operational layer the traffic flow is random, the 3D response was achieved (on the right)



Ideal queueing length approaching uniform density



3D Response Plot of the Queue Length Dynamics for a Single Intersection Control

Performance Potential for Intersection Control with Advanced Infrastructure Sensing (TASK-4)

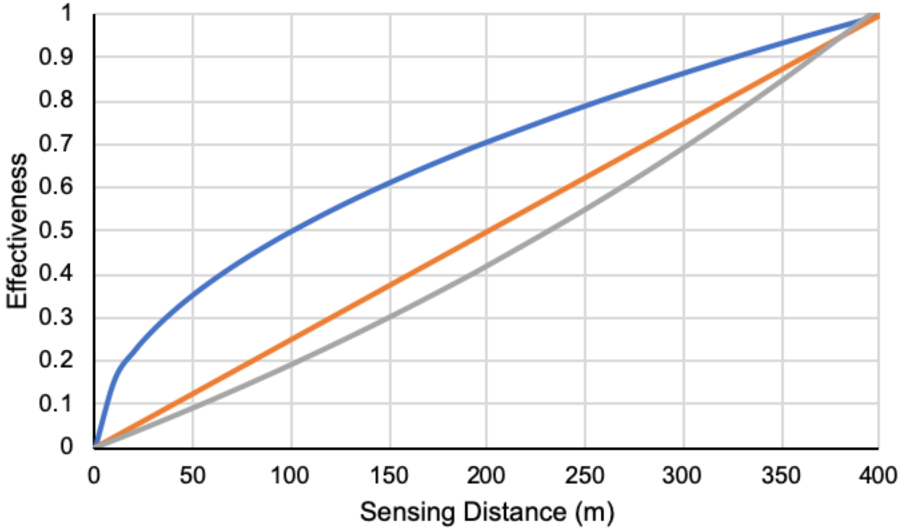
- Advanced spatial sensing technologies
  – Vehicle positions and speeds at intersections
- Facilitation of advanced control algorithms using sensor data in lieu of connected vehicle data at high penetration rates
- Explore the performance envelope for different sensing ranges
- Greater sensing range will improve the performance, but probably will reach diminishing returns at some point
- Approach:
  – Develop a simulation framework that incorporates the vehicle position and speed data into the control mechanism
  – Identify algorithms for intersection control that can leverage the data and incorporate these into the system
  – Vary the distance at which vehicles can be seen on the approach and see how the performance varies as a function of this

Performance Potential for Intersection Control with Advanced Infrastructure Sensing

- Approach:
  - Develop a simulation framework that incorporates the vehicle position and speed data into the control mechanism
  - Identify algorithms for intersection control that can leverage the data and incorporate these into the system
  - Vary the distance at which vehicles can be seen on the approach and see how the performance varies as a function of this

Anticipated Results:

- Sensitivity analysis – Determine relationship between sensing distance and effectiveness of control
- linear, exponentially growing in Effectiveness, and or asymptotically approaching 100% where “100%” means the effectiveness at infinite sensing range.



Approach: First-order approximation of energy equivalence of safety at intersections (TASK-4)

- **Crashes at Intersections**
  - In the United States, nearly 50% of crashes occur at intersections (NHTSA 2018).
  - Intersection crashes caused 8,682 fatalities, over 2.2 million injuries, and over 10 million damaged vehicles in 2010

- **Advanced technologies to reduce traffic collisions and improve traffic flow**
  - Connected and automated vehicle (CAV) technologies
  - Spatial sensing technologies (such as LiDAR sensing)
  - Eco-routing/driving, traffic coordination
  - Signal timing optimization

Approach: First-order approximation of energy equivalence of safety at intersections (TASK-4)

- A framework for estimating the GDP-weighted energy equivalence (EES) of safety at intersections
  - Combined with the economic value of crash impacts, it is possible to estimate the total energy costs related to all crashes, which can be further broken down by crash severity and location.

$$\boldsymbol{Energy\ equivalence\ of\ safety} \\ = \boldsymbol{Economic\ cost\ of\ safety}\ (\$) * \boldsymbol{Energy\ equivalent\ rate}(\boldsymbol{BTU}/\$\ \boldsymbol{or\ GGE}/\$)$$

*British thermal units (BTU); gasoline gallon equivalence (GGEs)

– Energy Equivalent Rates, using 2010 GDP and Energy Consumption Data

	National level
GDP ($M)	14,964,400
Energy Consumption (Quadrillion BTU)	98
Energy Equivalent Rate (BTU per GDP)	6,549 BTU/$
Energy Consumption (Billion GGE)	859.6
Energy Equivalent Rate (GGE per GDP)	**0.0574 GGE/$**

Approach: First-order approximation of energy equivalence of safety at intersections (TASK-4)

- GDP-weighted energy equivalent of crashes is worth slightly over 1/3 of the total U.S. gasoline consumption in 2017
- Costs per crash are much higher for the more severe crashes.
  - A first-order estimation of the energy costs per crash gives values of 571,819 GGE, 8,939 GGE, and 338 GGE for fatal, injury, and PDO crashes, respectively.
- GDP-weighted energy equivalence of safety at intersections account for 26% of fatal crashes, 57% of injury crashes, and 55% of PDO crashes

All Roads			
	Fatal	Injury	PDO
Number of crashes on all roads	30,296	2,969,963	10,565,514
Direct Energy Cost (GGE) per crash	10,987	1,710	382
HC Energy Cost (GGE) per crash	76,475	694	6
WTP Energy Cost (GGE) per crash	484,357	6,536	N/A
Total Energy Cost (GGE) per crash	**571,819**	**8,939**	**388**
Intersections			
# of person–vehicle crashes	8,682	4,829,008	10,127,014
# of crashes equivalence	7,971	1,686,345	5,780,930
% of crashes at intersections	**26%**	**57%**	**55%**

[5] L Zhu, S, Young and C. Day, Exploring First-Order Approximation of Energy Equivalence of Safety at Intersections, appearing in proceedings of ASCE International Conference on Transportation and Development (ICTD), 2019.

Technical accomplishments

[1] S M A Bin Al Islam, Ali Hajbabaie, H M Abdul Aziz, A scalable and real-time approach for optimal signal control in a semi-connected vehicle environment, Presented at 2018 INFORMS Annual Meeting, November 4-7, Phoenix, Arizona, USA.

[2] S M A Bin Al Islam, H M Abdul Aziz, Ali Hajbabaie. A Machine Learning Based Signal Control Algorithm with Energy Minimization Objective, Presented at 2018 INFORMS Annual Meeting, November 4-7, Phoenix, Arizona, USA.

[3] S M A Bin Al Islam, H M Abdul Aziz, Ali Hajbabaie. (2019) Stochastic Gradient-based Optimal Signal Control with Energy Consumption Bounds, Submitted for publication (*in review*).

[4] Islam, SMA Bin Al., H M Abdul Aziz, Ali Hajbabaie (2019) Traffic signal optimization with mobility and energy goals: a stochastic perturbation approach with distributed architecture (working paper)

[5] L Zhu, S, Young and C. Day, Exploring First-Order Approximation of Energy Equivalence of Safety at Intersections, appearing in proceedings of ASCE International Conference on Transportation and Development (ICTD), 2019.

On-going Tasks for FY19

- Sensitivity analyses of different powertrain vehicles: BEV, PHEV, and HEV [complete by Q3]
- Large-scale implementation of gradient-approximation based distributed control [complete by Q4]
- Modelling and control for 20+ intersections is being developed using multi-input and multi-output stochastic distribution control theory [complete by Q4]
- Simulation verification for the modelling and control strategy with collaboration of University of Washington and University of Virginia [complete by Q4]

Any proposed future work is subject to change based on funding levels

Response to Previous Year Reviewers' Comments
(Only the critical comments are addressed)

Question 1: Proposed Future Research

Reviewer 3: "It appeared to the reviewer that there needs to be a specific strategy for the machine learning application with the VisSim processing time for large-scale network models. "

Response: We agree with the reviewer. VISSIM is not suitable for distributed simulation. For large networks, we are utilizing mesoscopic spatial queuing based models such as cell transmission model (CTM) and planning to demonstrate its applicability for a network of 20 intersections. Likewise, the learning can done with traffic state estimation from in an efficient manner.

Reviewer 4: "The reviewer noted that planned ongoing (Slide 18) and future work (Slide 21) fails to consider more practical questions, such as performance under less-than complete vehicle penetration of DSRC and impacts of HEV/PEV powertrains, which differ significantly from internal combustion engine (ICE) cars in the stop-and-go environment under question. The reviewer said that no plans for a real-world—or even real-vehicle—testing are discussed.

Response: Great suggestion. We have incorporated the impact of market share of CAV-- *performance under less-than complete vehicle penetration of DSRC and impacts of HEV/PEV powertrains*—in FY19 tasks and initial results are presented.

Question 4: Technical Accomplishments and Progress toward overall project goals

Reviewer 4: "The reviewer expressed concern of the case study turn-around time to apply the reinforcement learning methodology, saying it will become much more difficult with the significantly more complicated large-scale traffic networks that are needed. The reviewer stated that this simple fact could jeopardize the schedule as the whole analytical process slows down, and strategies to address this issue would be important to address if the researchers agree this is a problem."

Response: Large-scale implementation will be a challenge for both learning-tuning-training and overall complexity in the computation. Our approaches will explore the use of simpler but realistic physical queue based traffic mode to estimate the traffic state which is more efficient compared to Vissim. We are working on developing distributed algorithm using the Cell Transmission Model—mesoscopic traffic model. In addition, we will explore the possibility to use HPC resources available to the national labs.

Partners/Collaborators

- Oak Ridge National Laboratory (Lead)
  - Washington State University, University of Washington, University of Virginia (subcontract and summer interns)
- National Renewable Energy Laboratory
  - Stanley Young (PI for the *Urban Science* pillar and providing directions for the project goals and active tasks)
  - Iowa State University (sub-contract)

Remaining challenges—Develop control with partial observability and accounting for EVs

- Development of control algorithms accounting for market share—partial observability of the traffic state
- Include all system users in the control—pedestrian priority based control
- Development of RL algorithms where the state accounts for the presence of difference in powertrain—HEV, EV, ICE, and so on

Less than 100% effectiveness in infrastructure sensing

Less than 100% CAV market share

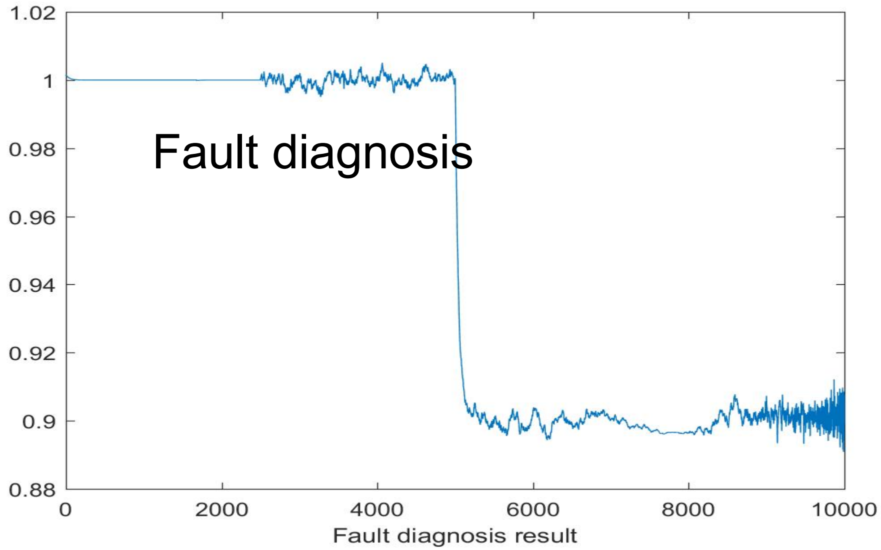
→ Partially-observed state → Partially-observed Markov Decision Process → Reinforcement learning based solution

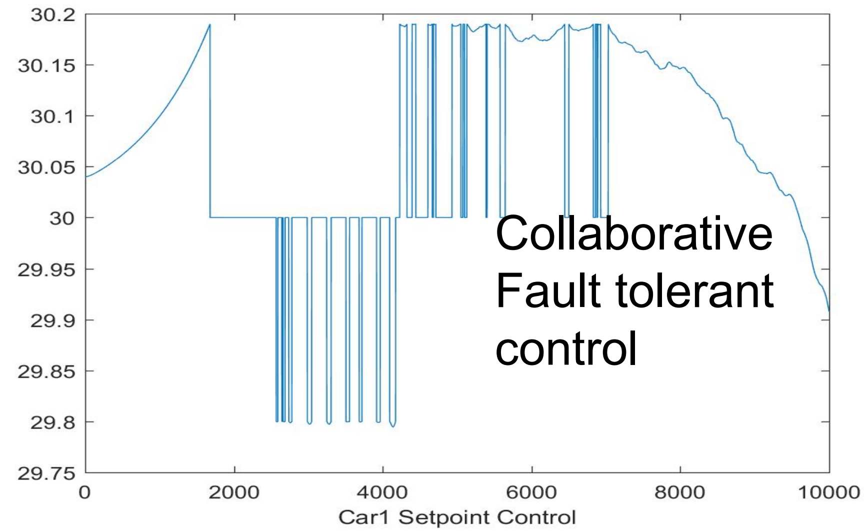
Any proposed future work is subject to change based on funding levels

Remaining Challenges: collaborative fault tolerant control with 100% CAVs

With 100% CAVs penetration, signalized intersections becomes non-signalized ones

- With 100% CAVs, communications of V2V allow vehicles to pass through smoothly with safety constraints
- Fast fault diagnosis for each CAVs, and collaborative fault tolerant control is required via V2V communication ([1] – [2]).





[1] H Wang, H Aziz, S Young, Non-Signalized Intersections Control – a Collaborative Fault Tolerant Control Perspective, talks at the International Conference on Transportation and Development, Pittsburgh, PA, 2018

[2] H Wang, Collaborative Fault Tolerant Control for Complex Systems - An Example of Non-signalized Intersection with CAVs , 1st International Conference on Smart Tourism, Smart Cities and Enabling Technology (The Smart Conference), Orlando, Florida, USA, 2019(invited)

Proposed future research

Type	Timeline	Milestone	Deliverables	Status
Proposed	FY20Q2	Develop a ***Partially-Observed-Markov-Decision-Process based reinforcement learning (POMDP-RL)*** algorithm to account for low penetration rate of CAVs [ORNL]	Report/Paper	In Planning
	FY20Q4	Implement and demonstrate the usability of the developed POMDP-RL algorithm [ORNL]	Report/Paper	In Planning
	FY20Q4	Develop initial control and optimization framework for ***pedestrian-priority based*** intersection control [ORNL]	Report	In Planning

Any proposed future work is subject to change based on funding levels

Summary

Relevance

- ❑ Assess the mobility and energy impacts of less than 100% CAV market share on the performance of developed machine-learning based control,
- ❑ Quantify the benefits of observability from spatial sensing at intersections.

Approach (FY19)

- ❑ Statistical analyses of impact of CAV penetration rate on signal control performance
- ❑ Distributed control with gradient approximation techniques
- ❑ GDP-weighted energy equivalence (EES) of safety at intersections

Technical Accomplishments

- ❑ Completed analyses on assessment of CAV market share impact
- ❑ Five scientific outputs (please see slide 19)

Proposed future research (FY20)

- ❑ Develop a *Partially-Observed-Markov-Decision-Process based reinforcement learning (POMDP-RL)* algorithm to account for low penetration rate of CAVs
- ❑ Develop initial control and optimization framework for *pedestrian-priority based* intersection control

Any proposed future work is subject to change based on funding levels

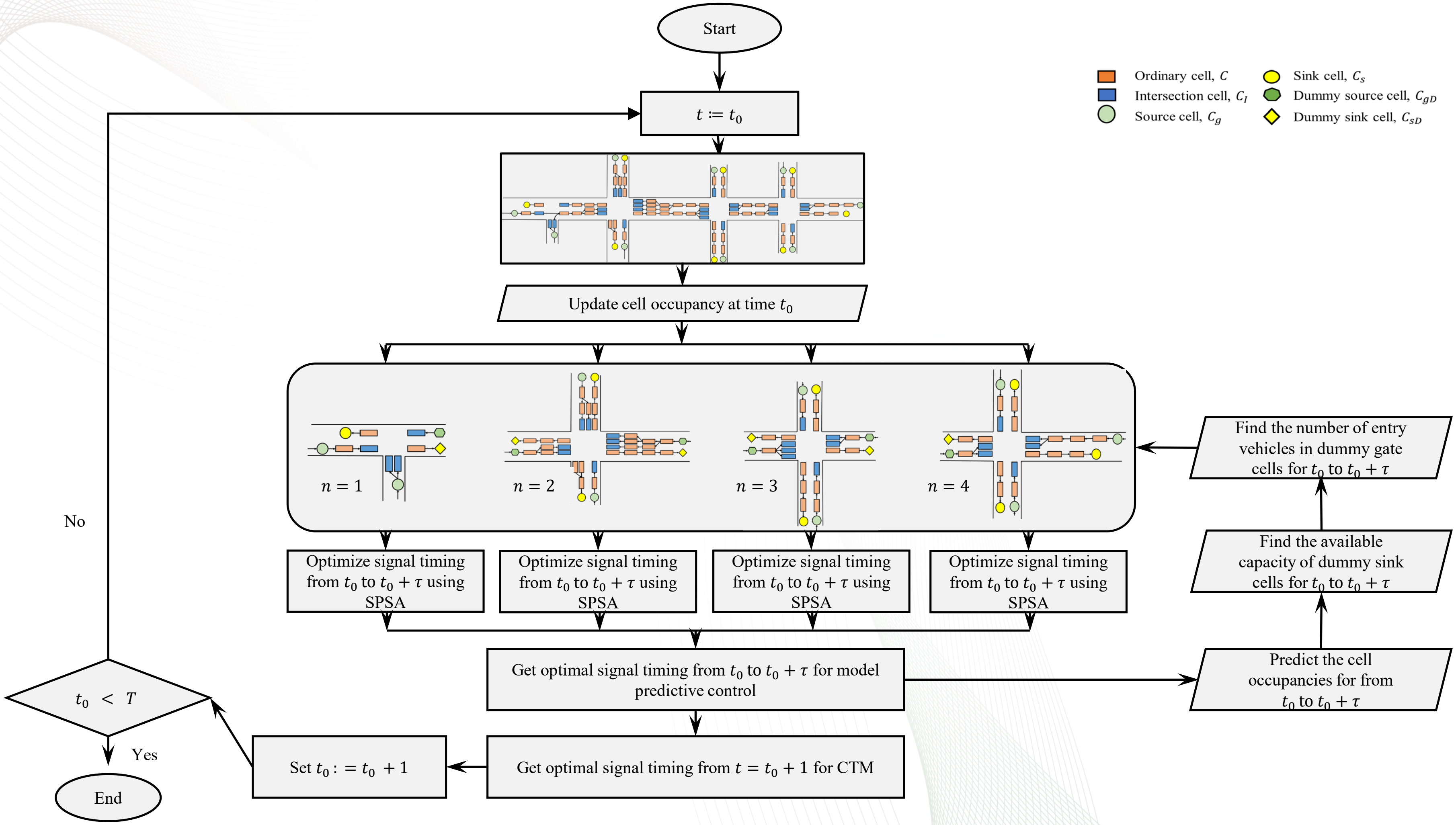
Questions/Comments

This research is funded by the Energy Efficient Mobility Systems (EEMS) Program of the Vehicle Technologies Office, Department of Energy and the team appreciates the support and guidance provided by DOE program managers

Technical Backup Slides

Distributed signal control using SPSA—(TASK-2)

Cite as: Islam, SMA Bin Al., H M Abdul Aziz, Ali Hajbabaie (2019) Traffic signal optimization with mobility and energy goals: a stochastic perturbation approach with distributed architecture (working paper)



Approach: First-order approximation of energy equivalence of safety at intersections (TASK-4)

- **Economic impacts of crashes include both direct and indirect costs**
- **Direct costs**
  – tangible and internal costs directly attributable to crashes, including costs related to property damage, medical rehabilitation, and induced congestion.
- **Indirect costs -** *not* directly linked to crashes, including two components:
  – **Human capital** (HC) cost is the person-correlated cost associated with loss of long-term future net production (i.e., the difference between future production and future consumption) due to the loss of work capability
  – **Willingness-to-pay** (WTP) cost is the price that a society (or a person) is willing to pay to avoid the risk and occurrence of fatal and injury crashes.

Type	Items
Direct impacts	Medical costs
	Emergency medical services (EMS)
	Lost productivity (immediate)
	Workplace losses
	Insurance administration costs
	Legal and court expenses
	Congestion costs
	Property damage costs
Indirect impacts	HC cost
	WTP cost

Approach: First-order approximation of energy equivalence of safety at intersections (TASK-4)

- Three types of energy costs in the energy equivalence of safety framework
  - **Direct energy costs** - consequences directly linked to the crash
    - fuel wasted during induced congestion; energy expended to repair property damage or lost embedded energy of totaled vehicles; energy impacts of medical rehabilitation; societal, legal and court expenses in energy
  - **HC energy costs -** reflect the energy equivalent productivity lost as a result of injury or death
    - The energy equivalent of such loss reflects the associated lost energy productivity, and the loss of quality of life (or correspondingly, the energy capital that would need to be spent to make up for the lost economic productivity)
  - **WTP energy costs -** indicate the energy equivalence of economic cost that society (or a person) is willing to pay to avoid the risk and occurrence of injury and fatality crashes.

Performance Potential for Intersection Control with Advanced Infrastructure Sensing

- Approach:
  - Develop a simulation framework that incorporates the vehicle position and speed data into the control mechanism
  - Identify algorithms for intersection control that can leverage the data and incorporate these into the system
  - Vary the distance at which vehicles can be seen on the approach and see how the performance varies as a function of this
- Tentative framework for modeling the system:
  - (Still in development)